Towards Using the Critical Decision Method for Studying Visualisation-Based Decision-Making

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ABSTRACT

Visualisations provide significant support for effective reasoning and decision-making processes. Its value mainly lies in its ability to turn raw data into actionable insights that lead to a decision. This requires appropriate visual representations that are designed with the decision-maker's way of reasoning in mind. Understanding the cognitive aspects underlying decision-making with visualisations is therefore crucial. Cognitive task analysis methods have been used to elicit expert knowledge in a variety of decision-making scenarios, with the Critical Decision Method (CDM) focusing on the cognitive bases in naturalistic non-routine incidents. In this study, we aim to determine the feasibility of CDM for capturing the expert knowledge, strategies, and cues involved with visualisation-based decision-making processes. Based on an analysis of four semi-structured interviews, we evaluate the method's potential to inform the role of visualisation for human decision-making. We anticipate that our reflections on methodological insights can serve as a starting point for other human factors and visualisation researchers, who aim at studying strategies for higher-level decision-making and problem-solving tasks.

KEYWORDS

Critical decision method, cognitive task analysis, interactive visualisation, decision-making

Introduction

Visualisation is used in many fields like engineering, meteorology, or medicine to help scientists understand the characteristics of a physical system. By visually communicating different types of (complex) information, domain experts are enabled to explore and interpret a system's underlying principles and structures (Haber, 1990). In engineering design, insights conveyed by visualisations are often used for the purpose of decision-making at different scales. However, the way people perceive a visualisation and interact with it can strongly affect their understanding of the system that is subject to their investigation. The role of human factors in visualisation thus deserves particular attention (Tory & Moller, 2004; Valdez et al., 2016; Torsney-Weir et al., 2015). To develop visualisation techniques that are effective, we need to better understand the cognitive processes that are at the core of decision-making with visualisations [Padilla, 2018].

Task analysis is a technique commonly used in the human factors domain to understand the interaction between a system operator and a system. Using the task analysis method, the interaction is broken down into individual steps, including a detailed description of the required actions of the system operator (Kirwan & Ainsworth, 1992). However, traditional task analysis techniques only cover observable actions exhibited by the system operator and do not describe the underlying cognitive processes. This gave rise to the development of cognitive task analysis methods. The Critical Decision Method (Hoffman et al., 1998; Klein et al., 1989) is one of them. It has been applied for various purposes, such as studying novice/expert differences, eliciting trainee and expert mental models, making collaborative decisions, developing training and decision aids, or identifying workstation and interface features that facilitate decision making. The higher-order goal is to capture the expert knowledge and experience involved in real-world decision making and problem solving.

The starting point of the Critical Decision Method (CDM) is an interview, in which a diverse team of interviewers aims at eliciting information about cognitive processes, such as decision making, planning, and sensemaking, within a specific incident. The overall strategy for the interview is to gradually focus on critical cognitive points by revisiting the incident multiple times. The interviewer team aims at obtaining a detailed description of the incident and a thorough understanding of the involved cognitive functions. The interview is usually conducted in four stages (Crandall et al., 2006). In the first stage, an interviewee is requested to provide a brief account of the incident, from beginning to end. The second stage is about obtaining a clear and refined overview of the incident structure as well as identifying key events and segments. The third stage goes beyond the pure time elements by asking for the interviewee's perceptions, judgments, and uncertainties about the incident as the event unfolded. The final stage comprises hypothetical questions, using the incident as a springboard, as well as further questions targeting particular aspects of the incident.

In the visualisation domain, design studies have become the essential approach to conducting problem-driven visualisation research (Sedlmair et al., 2012). Various methods like interviews and observational studies have been employed to study the domain experts' real-world work environments and practices (Lam et al., 2012). Still, there are voices calling for increased rigor in design studies to achieve a broader collection of knowledge (Meyer & Dykes, 2019). However, to the best of our knowledge, few, if any, design studies exist that adopt a formalised cognitive task analysis for the purpose of domain characterisation.

We aim to shed some light on this gap by investigating the CDM as a formal approach to understand how domain experts interact with visualisations when making multi-criteria decisions. Rather than developing a cognitive model or a visualisation concept, our focus is on the feasibility of CDM for characterising decision-making processes to serve as a solid ground for future visualization design. Therefore, we will mainly reflect on lessons learned and insights gained during the application of this method and only touch briefly on the actual results of applying the CDM. With our work, we contribute to the on-going adoption of human factors principles for problem-driven visualisation research by providing methodological reflections on the application of a cognitive task analysis method for characterising visualisation-based decision-making strategies.

Methodology

The overarching goal of our CDM study is to evaluate the method's potential to effectively elicit expert knowledge that can be used in a second step (beyond the scope of this work) to develop methodological guidelines concerning how visualisation can be used to improve decision-making by explicitly considering the cognitive aspects underlying the experts' reasoning. In this way, we aim to contribute to the body of work dealing with identifying domain-invariant principles for visualisation design. Figure 1 illustrates the detailed steps in our study.

Selected theme

We applied the CDM to analyse decision-making processes in the domain of engineering design. We selected multi-criteria optimisation as the main theme for our study because it is a key challenge in engineering design. Most designs need to simultaneously satisfy conflicting requirements, e.g. maximising vehicle performance while minimising fuel consumption and pollutants emission. A unique optimal solution to such problems does generally not exist. Instead, engineers need to decide for a compromise in a typically large solution space. Such multi-criteria choices are also of significant relevance in many other fields of science.

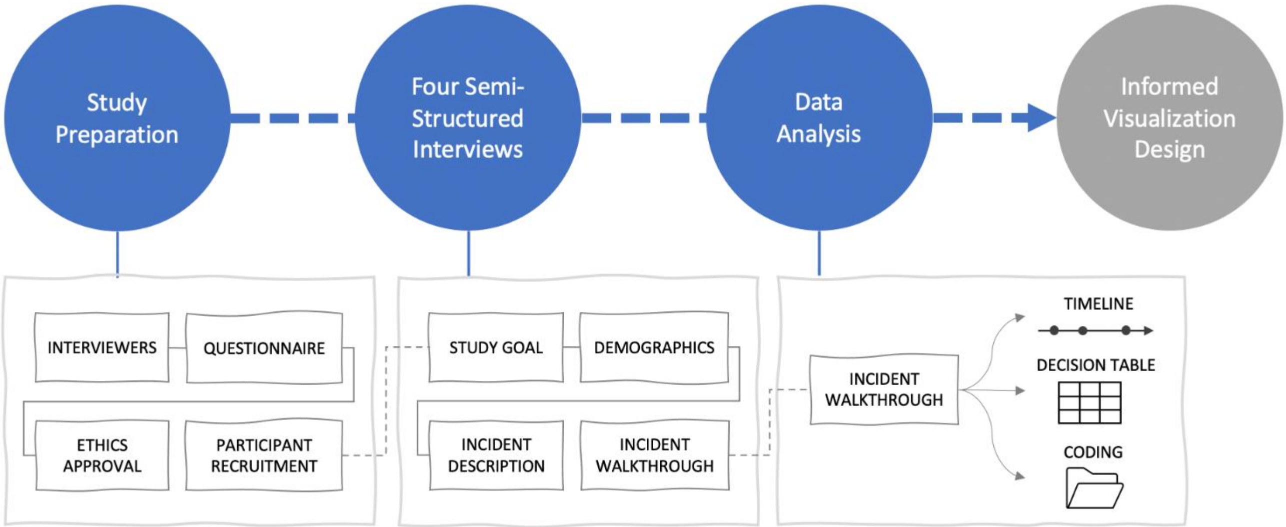

Figure 1: We follow three steps in applying the Cognitive Decision Method (CDM) to understand the cognitive aspects underlying decision-making with visualisation in engineering design. Study preparation involved setting up the interviewer team, compiling the questionnaire, applying for ethics approval and finally screening and recruiting participants. The 1.5-hour screen-captured interviews contained, besides a general introduction, open questions about the incident under observation followed by a think-aloud walkthrough. Analysing the observations resulted in three artefacts: 1) a timeline describing the situation assessment as a series of decision points together with metadata such as perceived cues and actions taken, 2) a table enriching the decisions that were made with contextual information, and 3) categories that describe common goals, needs, approaches and difficulties across participants. We anticipate that these artefacts hold the potential to inform the development of domain-invariant guidelines for designing visualizations that explicitly take cognitive aspects into account to support decision-making more effectively.

We did not specify any restrictions regarding particular engineering design applications, nor did we focus on selected approaches to multi-criteria optimisation. Many different optimisation approaches exist, each of them involving different steps in the decision-making process. Our intention was to reflect this wide breadth of approaches in our exploration. However, among the recruited participants, we observed two types of decision-making strategies: genetic optimisation and iterative design space exploration. Genetic optimisation is inspired by the process of natural selection, where a population of candidate solutions iteratively evolves towards superior solutions. However, with conflicting criteria, optimisation algorithms can only compute a number of Pareto-optimal solutions (solutions which contain some trade-off among the objectives). From there, it is the responsibility of the engineer to decide for the most-preferred compromise. Iterative design space exploration approaches are characterised by repeated design changes followed by an exploration of their effects until the engineer is satisfied with the result.

Interviewees and interviewing team

The study was performed with full-time employed engineers from different domains, whose daily work included multi-criteria optimisation. An additional prerequisite for participants was that they were familiar with visualising the (intermediate) results of their optimisation processes to make the final multi-criteria choice. We used convenience sampling and online recruitment to recruit participants for the study. Their involvement in the study was voluntary and we offered incentives to compensate for the participants' time. They were free to withdraw at any time and in case of withdrawal, we did not keep any of their data. Participants of the study had to meet the following criteria: 1) they were experienced in conducting multi-criteria optimisation projects with visualisation, 2) they had access to material related to such a project, and 3) they were willing to share their material during the interview. Volunteers were screened prior to the study to ensure that they meet these criteria.

Four participants were recruited for the interview. Participants were male, aged between 26 and 42, and their experiences in engineering design ranged from 4 to 15 years. Two participants used a genetic algorithm for multi-criteria optimisation, while the other two adopted an iterative design space exploration approach. All participants presented distinct engineering design cases: 1) optimisation of operation modes in a thermal power plant, 2) simulation-based optimisation of electric drives, 3) optimisation of an aircraft electrical power systems, and 4) simulation-based optimisation of a Francis turbine.

The interviewing team comprised three members: one human factors expert as the principal interviewer and two visualisation experts.

Interviews

We conducted the study as a series of 1.5-hour semi-structured remote interviews (via Skype). The interviews were recorded via screen capturing (Camtasia) and the interviewer team additionally took notes of the participants' answers to the questionnaire. In addition to open questions, the participants were requested to walk the interviewers through an exemplary project in engineering design to understand the cognitive process of the participant in deciding which solution in an optimisation setting is the most preferred one. The principal interviewer began each session by introducing the goal of the interview, which was to investigate the cognitive aspects underlying the engineer's decision-making process and how visualisation aided this process. Starting off with demographic questions and general questions about the type of design optimisation they typically dealt with, the participants were requested to provide a brief overview of their chosen multi-criteria optimisation project. At this stage, the participant described the process briefly with little interruption from the interviewers and covered the purpose of the product/system to be designed, the design parameters and criteria of the design, the varying importance of criteria etc. During this recitation, the interviewers primarily focused on understanding the story. At the following stage, the interviewer team asked the participants to replay their process of deciding for a preferred design solution by going through their material related to the multi-criteria optimisation in sequential order. Questions accompanying this walkthrough aimed at understanding what insights the interviewees gained at each step, what options they considered, why they considered these options as well as which visualisation helped this process and how. Answers to these questions provided a rich information regarding the particular optimisation conditions at each juncture.

Data Analysis

Upon completion of the interviews, we analysed our transcriptions and video recordings by following the Critical Decision Method according to Hoffman et al., 1998. This resulted in two primary artefacts: 1) a timeline describing the situation assessment as a series of decision points including goals, cues, experience, knowledge, and actions as well as 2) a detailed table specifying the particular decisions that were made, how they were made, why they were difficult to make, and what supporting information was used to make them. In addition to this, we also used a qualitative coding methodology (Strauss & Corbin, 1990) to identify common goals, needs, approaches, and difficulties that emerged from the responses of the participants. Each interviewer conducted the data analysis independently. The interviewers then assembled and reviewed the analysis results in a 2h remote discussion.

Results

Despite conducting the data analysis independently, the majority of results were found to be in agreement between the members of the interviewing team. The analysis results clearly showed the impact of the two different approaches to solving multi-criteria optimisation problems. With genetic algorithms, the navigation of the design space is performed by an automated systematic sampling of the design parameters. Thus, decision-making is primarily about selecting the most-preferred compromise from a set of alternatives that are known ahead of time. In contrast, with the iterative design space exploration approach, decision-making involves decisions about both where to go next in the design space as well as whether the currently observed solution sufficiently meets the criteria. Still, both approaches also showed commonalities. Soft knowledge and intuition, which originate from years of experience and expertise in the respective application field, played an important role for the way participants made sense of visual representations and used derived insights to guide their decision-making: *"by doing it interactively and taking advantage of the knowledge of the engineer, we come to an optimised solution much faster than by doing automatic design optimisation"* (P4). When observing a visualisation, they knew exactly what parts of the presented data to focus on and what information could safely be discarded. Another commonality lies in the challenge of handling the typically non-linear relationships underlying physical systems. Despite the distinct engineering design cases, the participants faced similar difficulties in searching for a compromise solution, where improving on a particular undesired property introduced unintended worsening regarding other properties: *"we find very often highly coupled effects, so correcting one problem sometimes creates an unexpected problem in another part of the system"* (P1) and *"if you improve the efficiency in one operating point, it might decrease in another"* (P4).

Discussion

Investigating how people extract information from data to make decisions under different circumstances is key to understanding how visualisation can contribute to better decision-making processes. Capturing the cognitive aspects that are associated with real-world problem-solving and decision-making strategies requires a careful consideration of human subjective characteristics, domain-specific knowledge, as well as the surrounding conditions like availability of options to consider or time pressure. This involves many aspects and dependencies that cannot be easily described by quantifying measures. Thus, a qualitative method like CDM is the tool of choice to extract meaningful information that can then be condensed into an abstract characterisation, taxonomy, or conceptual model to inform developments across application domains.

Despite being a qualitative method that requires participants to elaborate on their answers, compared to e.g. a multiple-choice survey, we found CDM to be a practicable approach that makes efficient and economical use of expert time (each interview session consumed less than two hours). The time-consuming part remains the responsibility of the researchers, who conduct the interviews and connect and transfer the collected information into general concepts. However, we consider this justified with regard to the richness of the responses that feed the generalisation. Still, a qualitative interview approach limits the number of participants and thus the representative character of the engineering design cases that can be covered.

A unique property of CDM is that the investigation is centred around an incident from the participant's own experience. This differs from task analysis approaches where the participants are confronted with unfamiliar tasks that are specified by the interviewers to account for comparability across participants and significantly reduce the ecological and psychological validity. In contrast, CDM allows the experts, not the interviewers, to choose a real-life decision-making scenario as the subject of investigation, in which their experience makes the strongest difference to solve challenging problems. This offers two major advantages. First, the participants are the experts regarding the discussed scenario and are thus able to provide a comprehensive review of the cognitive processes they go through during decision-making. Second, the impressions conveyed by the participants are collected without the bias that might otherwise be introduced by requiring them to learn about an unfamiliar task. At the same time, this approach leaves the interviewers fairly naïve about the discussed scenarios. Understanding the unfamiliar engineering design cases and their context on the fly thus places a significant mental demand upon the interviewing team, which we underestimated. Prior to the interviews, we only requested as much material from the participants as was needed to assess their suitability for the study. In hindsight, once the participants were deemed to be fit to be involved, we should have requested access to the complete material to familiarise ourselves with the incidents they were going to describe during the interview. Despite not being deeply involved in the engineering design cases presented, we successfully managed to identify junctures for decision-making and to probe them on the fly. However, we did not explicitly discuss the decision-making timeline and its relevant aspects during the interview. In retrospect, we should have included this either as a part of the interview or as a follow-up discussion after the interview as a form of verification of our analysis results. Additionally, we postulate that the mental demand for the interviewing team could be reduced by ensuring that the interviewers have either an educational background in engineering or experience in product and/or process optimisation. If this is not the case, a brief introduction to common principles of optimisation and some examples of their application in design and/or process optimisation would be helpful. However, we do not recommend an in-depth training for specific engineering design cases. This would be highly challenging for the interviewers, who have only a small to no background in optimisation. Thus, an in-depth training might overlook the purpose of understanding the general principles of optimisation.

Particularly for developing decision aids, CDM suggests conducting the situation assessment by describing the participants' reasoning activities using decision points that are enriched by a set of antecedents, like knowledge, experience, and critical cues, as well as goals and expectations. This is in turn complemented by a decision requirement table containing additional information on the surrounding conditions of each decision point. Gathering and sorting the information in this way turned out to be highly beneficial for our goal of studying the role of visualisation support in decision-making processes. Visualisations and associated interactions are highly task- and context-dependent. The identified decision points translate to individual contexts that might require different visualisations. The extracted goals and expectations hint at what the users of the visualisation want to do (not see), i.e. the analysis tasks they need to solve. Finally, the antecedents provide an idea of the influencing factors at each decision point, towards which a visualisation needs to be open.

One of the critiques regarding CDM is that methods that investigate retrospective incidents are commonly associated with concerns of data reliability originating from memory degradation. A central part of our study was the participants' walkthrough of a chosen multi-criteria optimisation project while recalling their decision-making processes. As mentioned above, the participants were free to choose any project of their daily work that they thought they knew well enough and felt comfortable with. The participants conducted the walkthrough process with the help of files that documented their decision-making process to solve the optimisation problem in the past, which aided their memory recollection. We thus argue that the risk of data reliability issues due to memory degradation is minimised and not significant in our case.

While only a limited number of participants were involved, they presented a variety of different engineering design cases as well as ways to address multi-criteria optimisation problems. Across these approaches, CDM allowed us to gain a detailed understanding of how domain experts extract information from visualisation to make decisions. Extrapolating these findings, we assume that CDM will also be applicable for approaches other than genetic algorithms and iterative design space exploration.

Conclusion

Human factors research is about understanding the interaction between a system operator and a system to optimise the operator performance. This also applies to domain experts using interactive visualisations for decision-making. Understanding the cognitive aspects underlying decision-making with visualisations is fundamental to inform visualisation design such that the information conveyed is indeed actionable by domain experts. To achieve this aim, we have proposed to use the Critical Decision Method (CDM). Our study has demonstrated the initial potential of CDM to provide insights regarding the role of visualisation at different decisive junctures. However, we also found that further refinement of our methodological approach is needed. Our future research will thus focus on establishing a more robust and standardised CDM process for investigation of the cognitive aspects behind visualisation-based decision making.

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